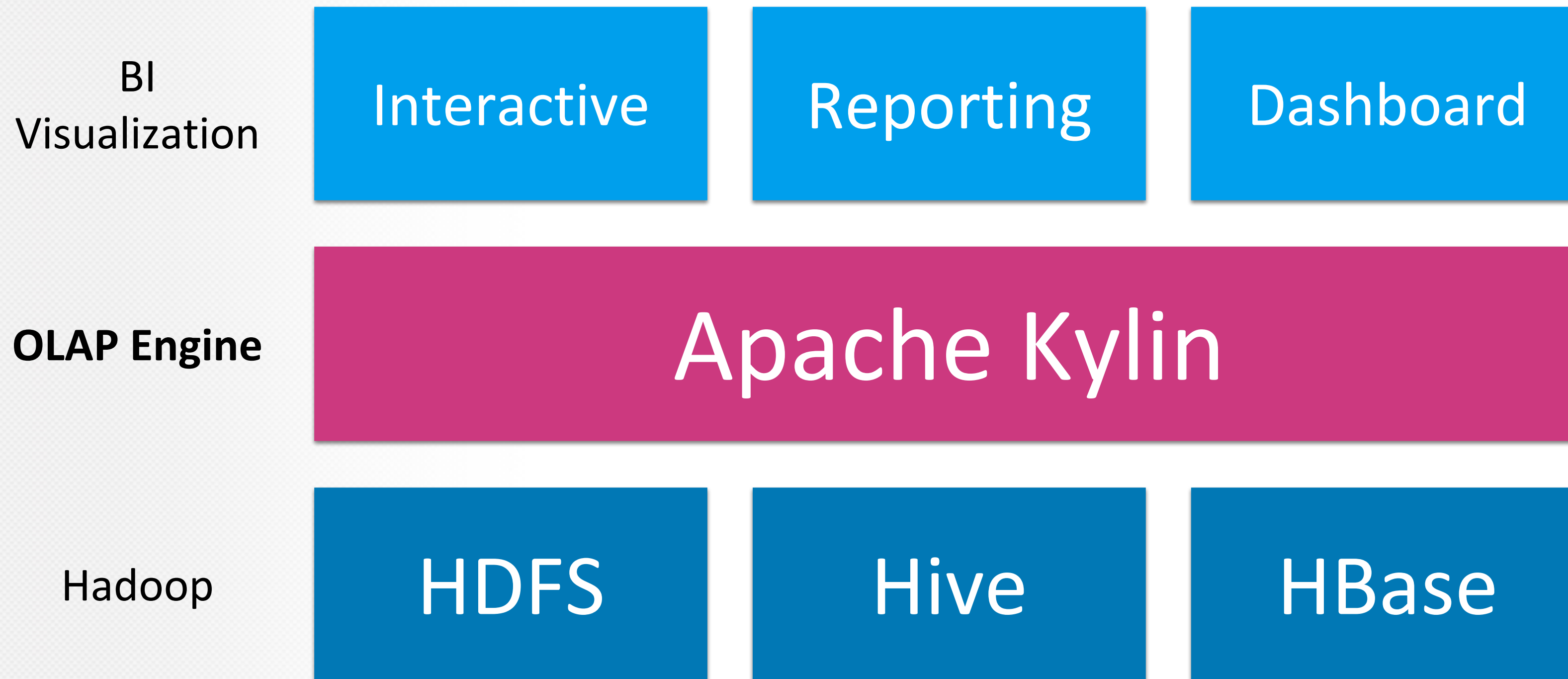


Apache Kylin v2.0 最新功能和深度 技术解读

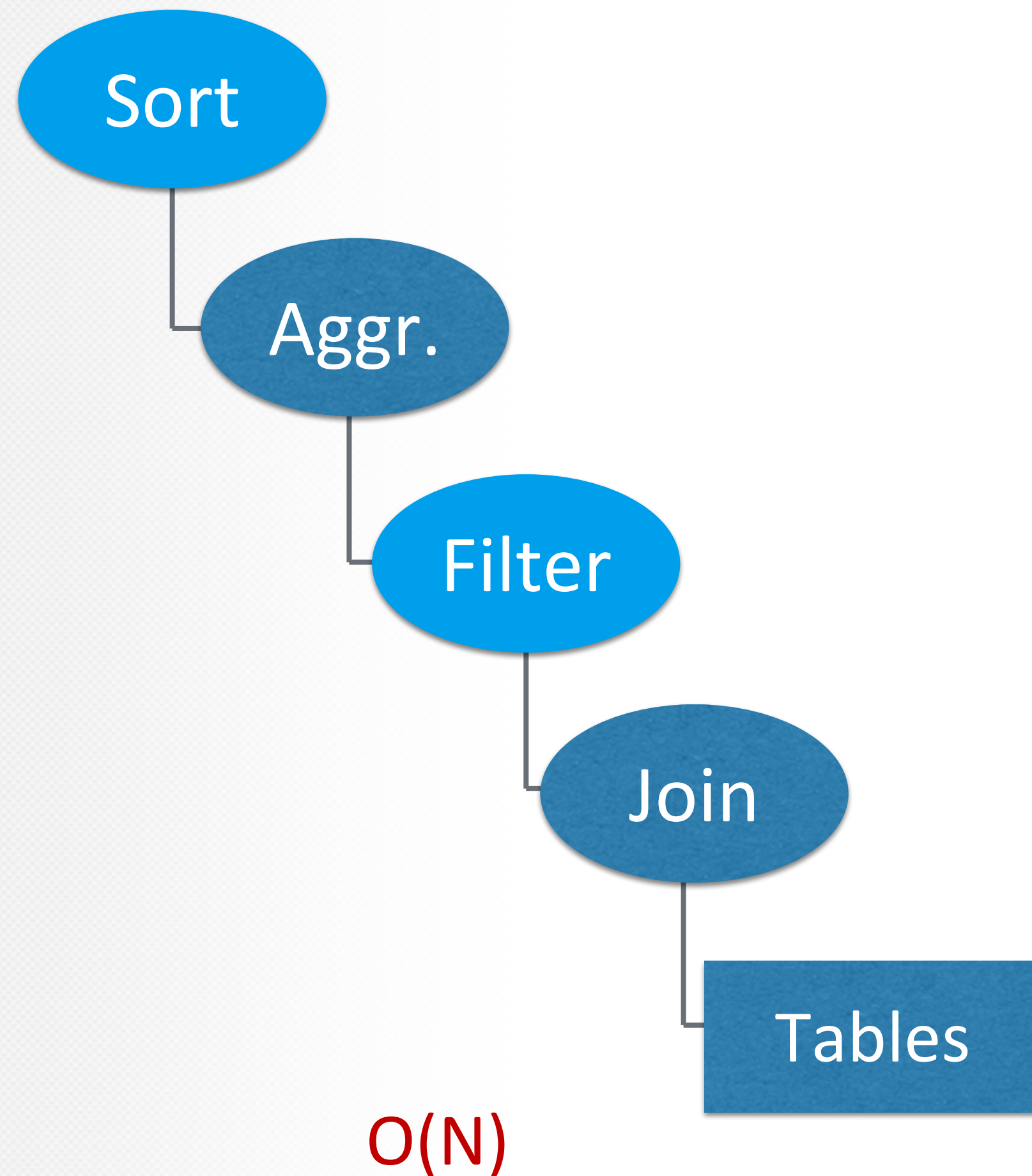
李扬 | Li, Yang
Co-founder & CTO

Apache Kylin是什么



- 3万亿行, 查询时间 < 1 sec
@toutiao.com, top 1 news feed app in China
- 60+ 维度 cube
@CPIC, top 3 insurance group in China
- JDBC / ODBC / RestAPI
- BI 无缝集成

Kylin 为什么快



一个例子: 给定时间范围, 按 “returnflag” 和 “orderstatus” 报告营收。

select

```
l_returnflag,  
o_orderstatus,  
sum(l_quantity) as sum_qty,  
sum(l_extendedprice) as sum_base_price  
...
```

from

```
v_lineitem  
inner join v_orders on l_orderkey = o_orderkey
```

where

```
l_shipdate <= '1998-09-16'
```

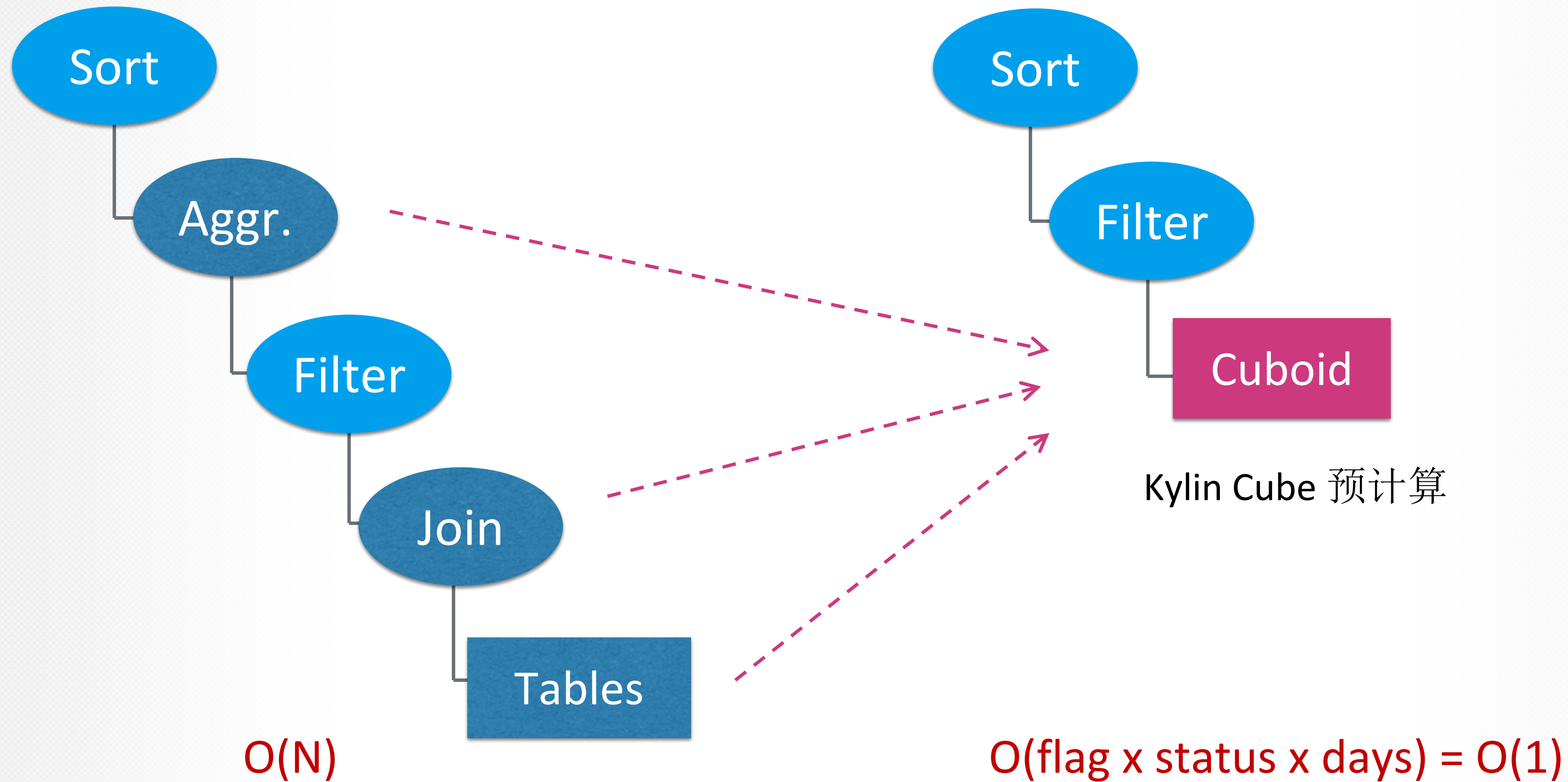
group by

```
l_returnflag,  
o_orderstatus
```

order by

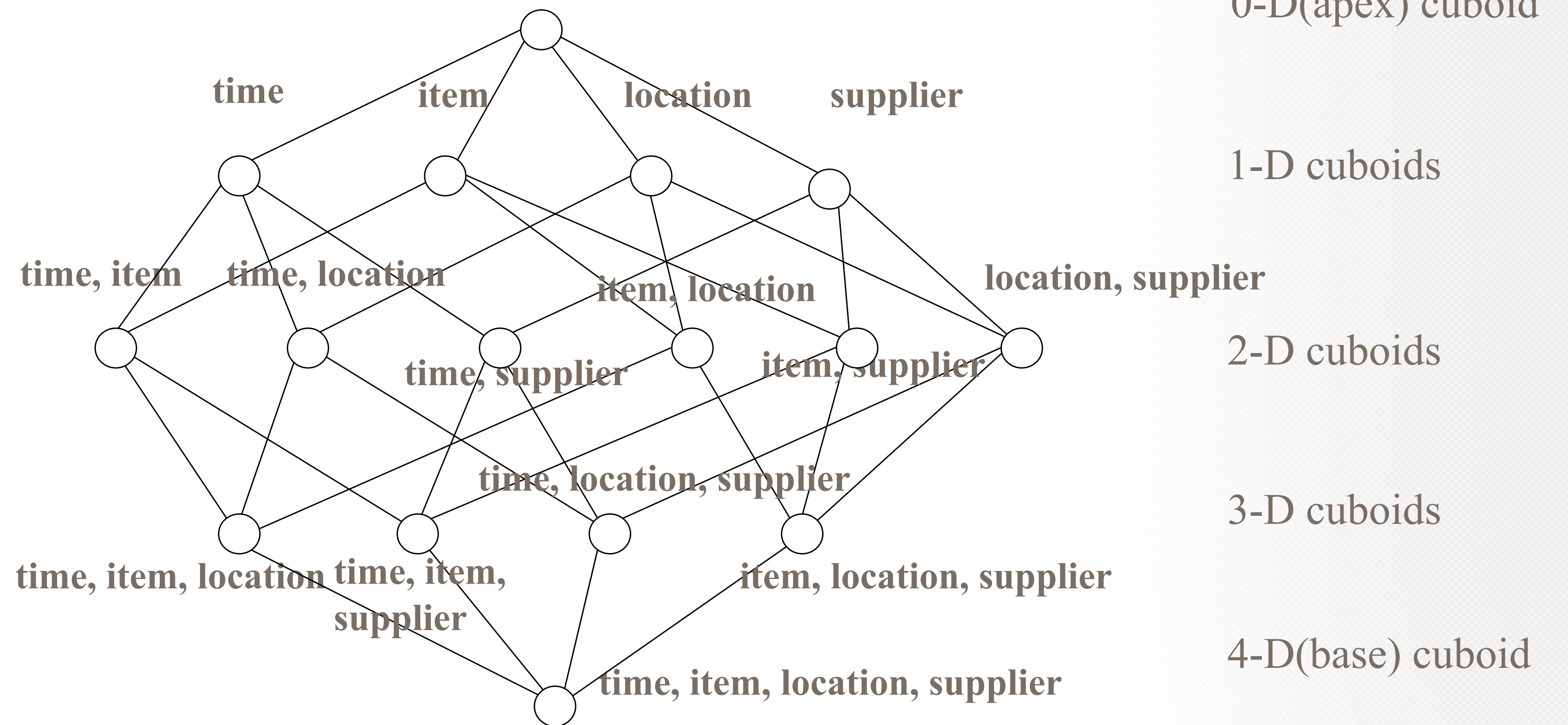
```
l_returnflag,  
o_orderstatus;
```

Kylin 为什么快

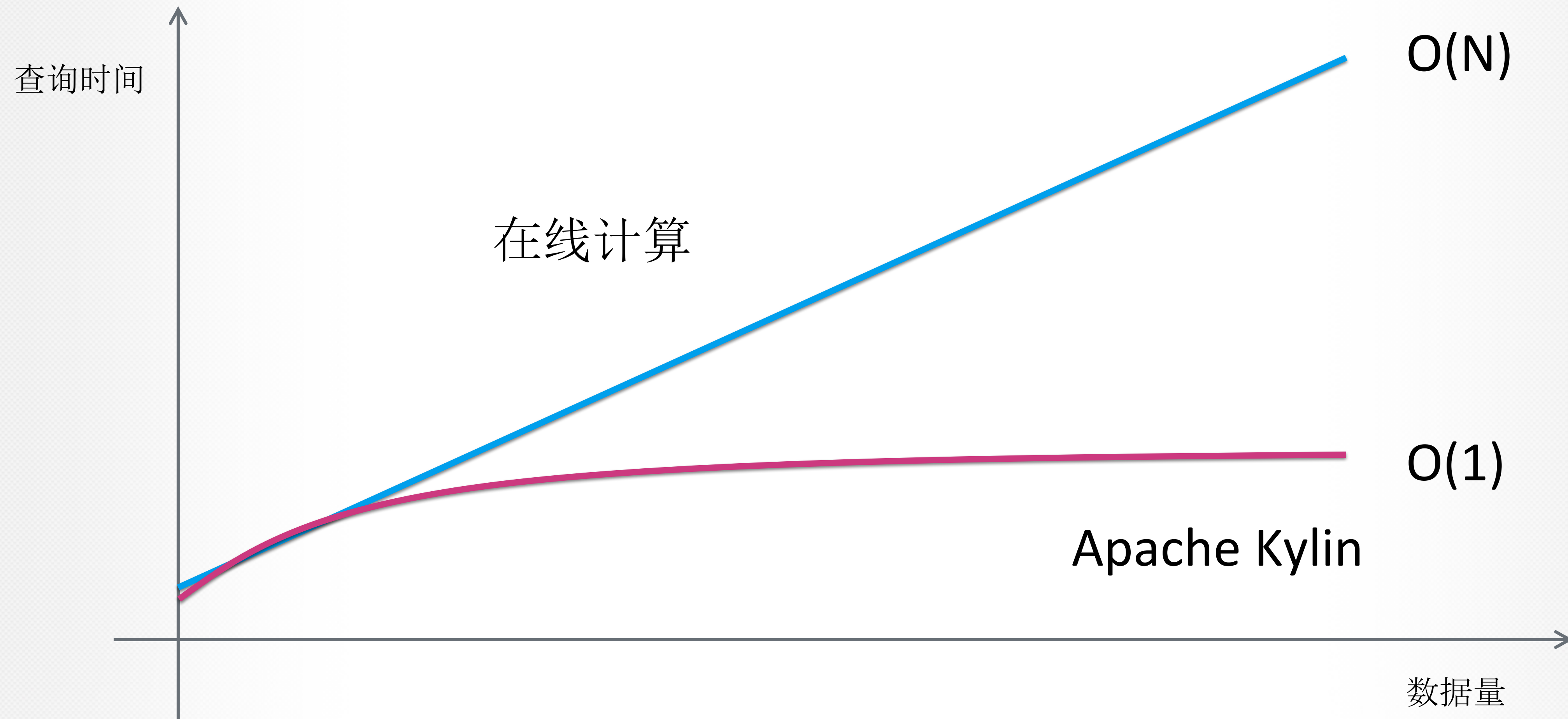


Kylin 就是预计算

- 基于 Cube 理论
- **Model** 和 **Cube** 定义了预计算空间
- **Build Engine** 执行预计算
- **Query Engine** 在预计算结果上执行 SQL



O(1) 无论数据多大





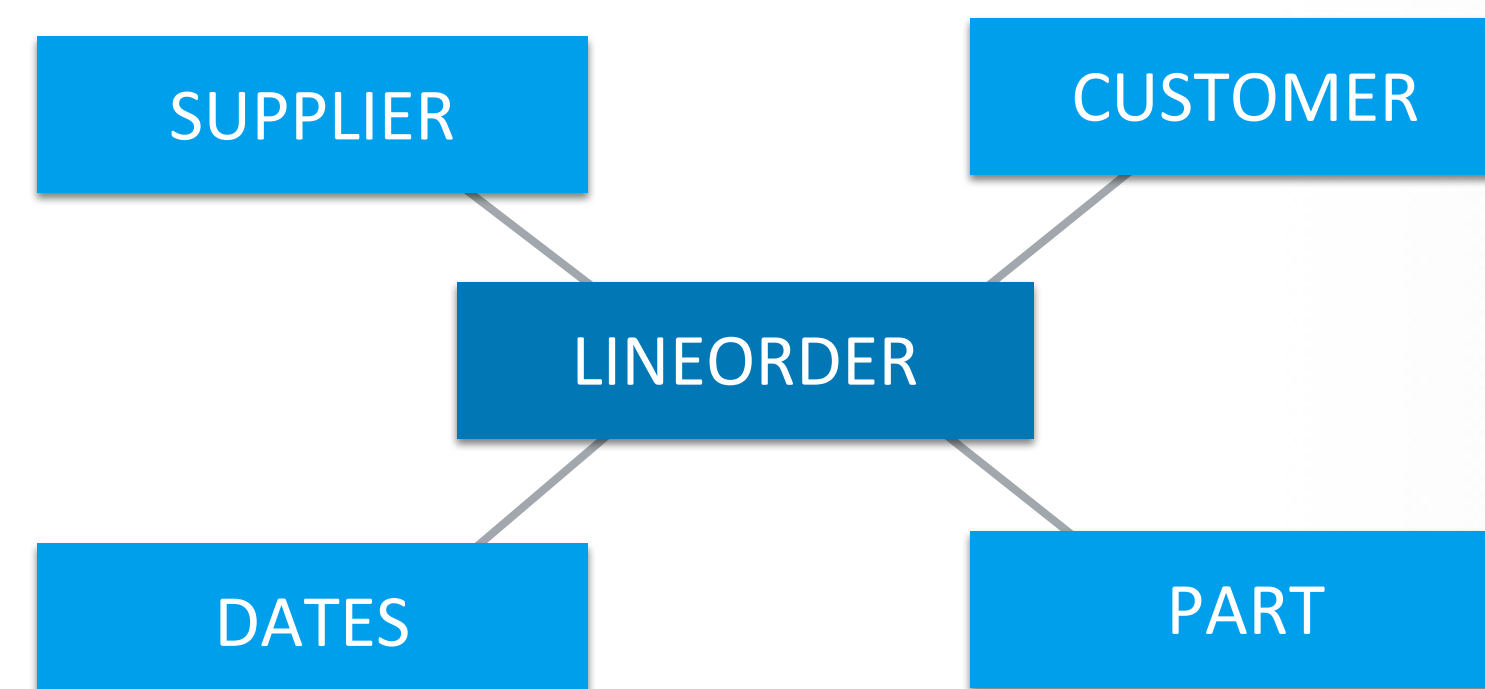
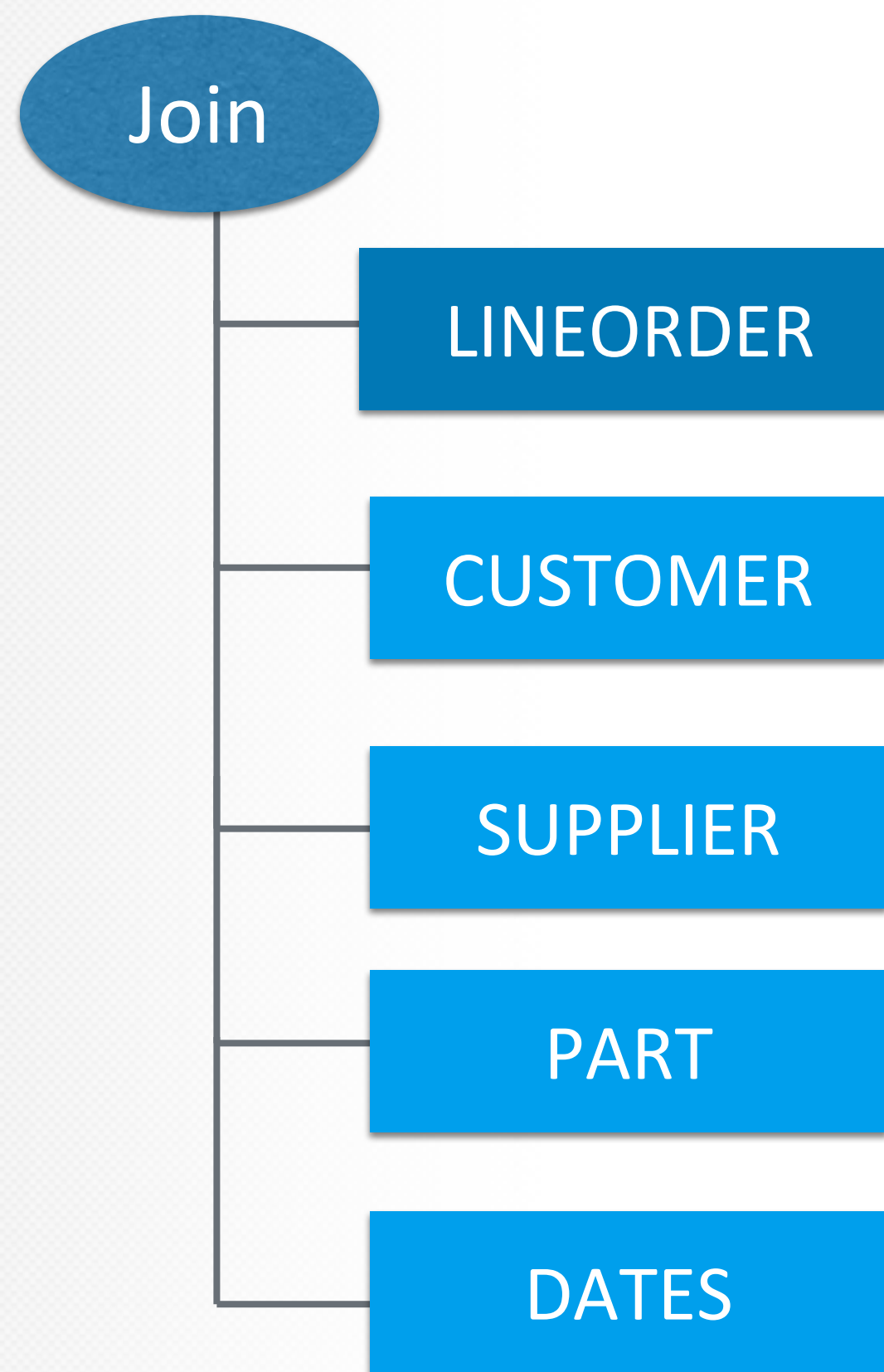
支持雪花模型

运行 TPC-H 基准测试

Kylin 1.0 受限于星形模型

只支持一层维表

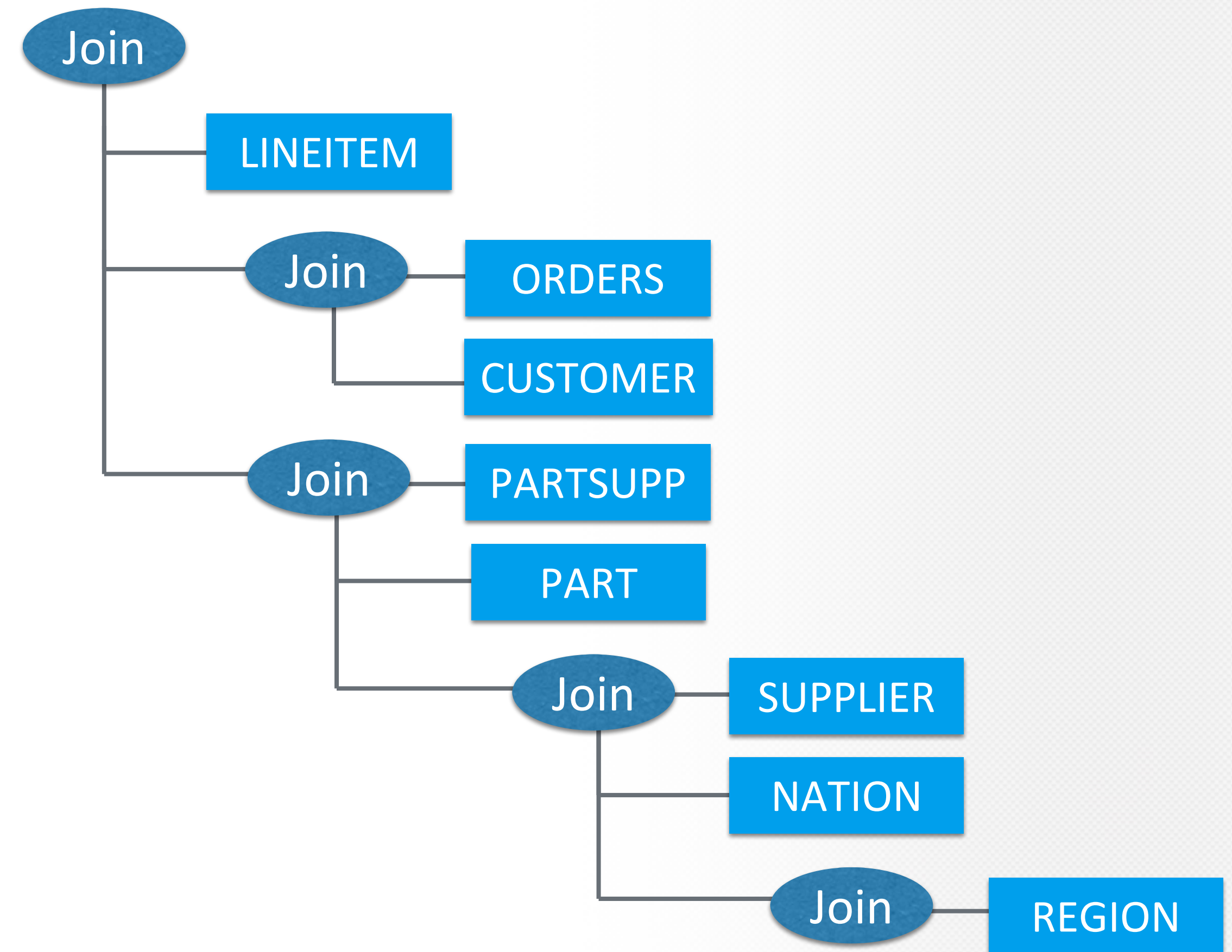
- 只支持星形模型
- 不允许同名列即使在不同的表上
- 不允许一张表关联自身
- 无法直接支持真实的业务场景



Kylin 2.0 雪花模型

支持多层维表

- 支持雪花模型 (KYLIN-1875)
- 支持同一张表被关联多次
- Model 的元数据有较大变化
- 修复了很多关于子查询和多表关联的缺陷
- 支持任意复杂的模型，任意灵活的查询



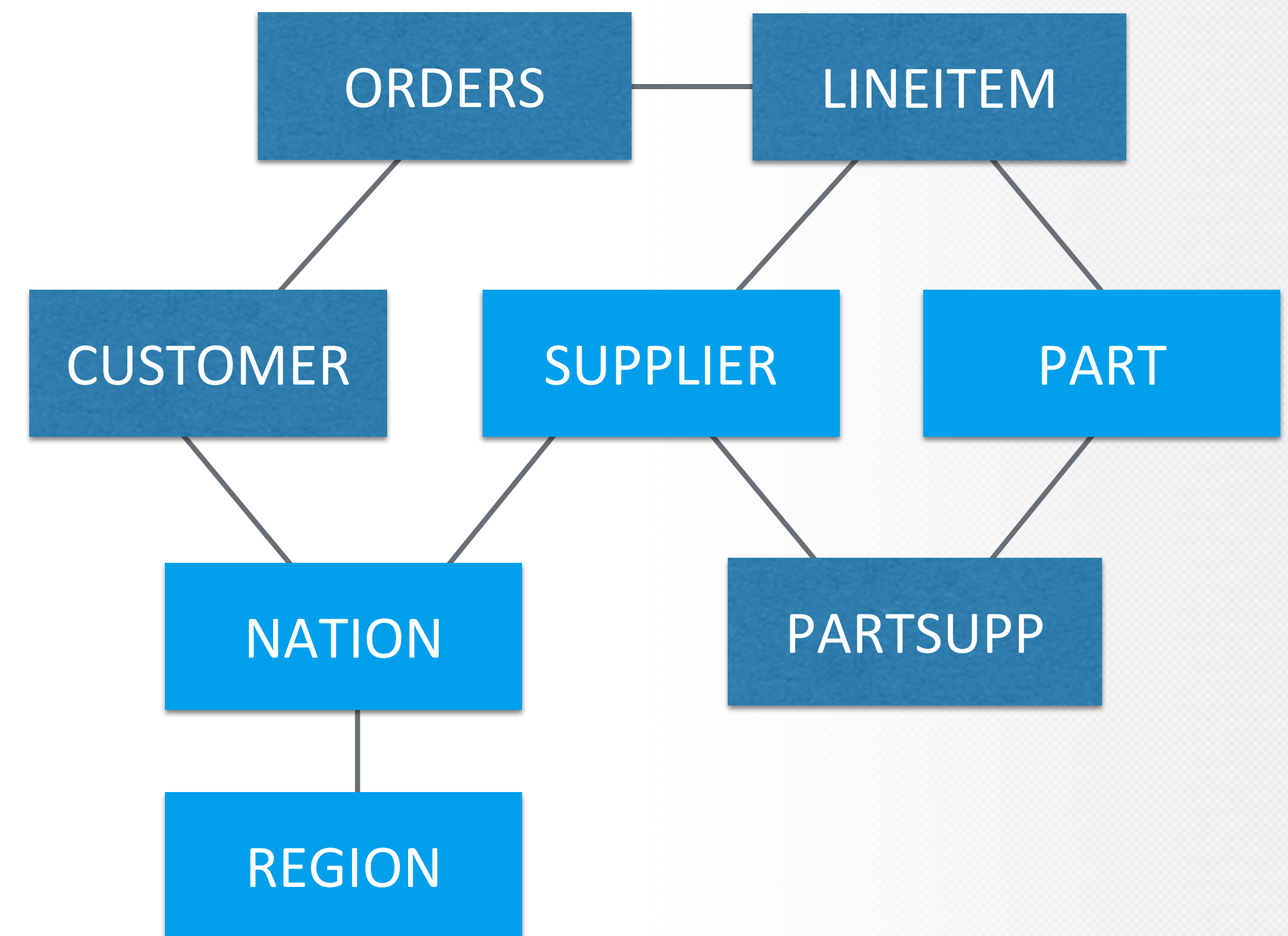
Kylin 2.0 上的 TPC-H 测试

TPC-H 是一个决策支持系统的基准测试

- 流行于商业 RDBMS 和 Data Warehouse 系统
- 查询和数据模型有广泛的行业普适性
- 分析大量数据
- 执行高复杂度的查询
- 回答关键的业务问题

Kylin 2.0 可以执行所有 22 条 TPC-H 查询 (KYLIN-2467)

- 通过预计算可以执行非常灵活和复杂的查询
- SQL 兼容性是现阶段的目标，而不是性能
- 具体步骤: <https://github.com/Kylogence/kylin-tpch>

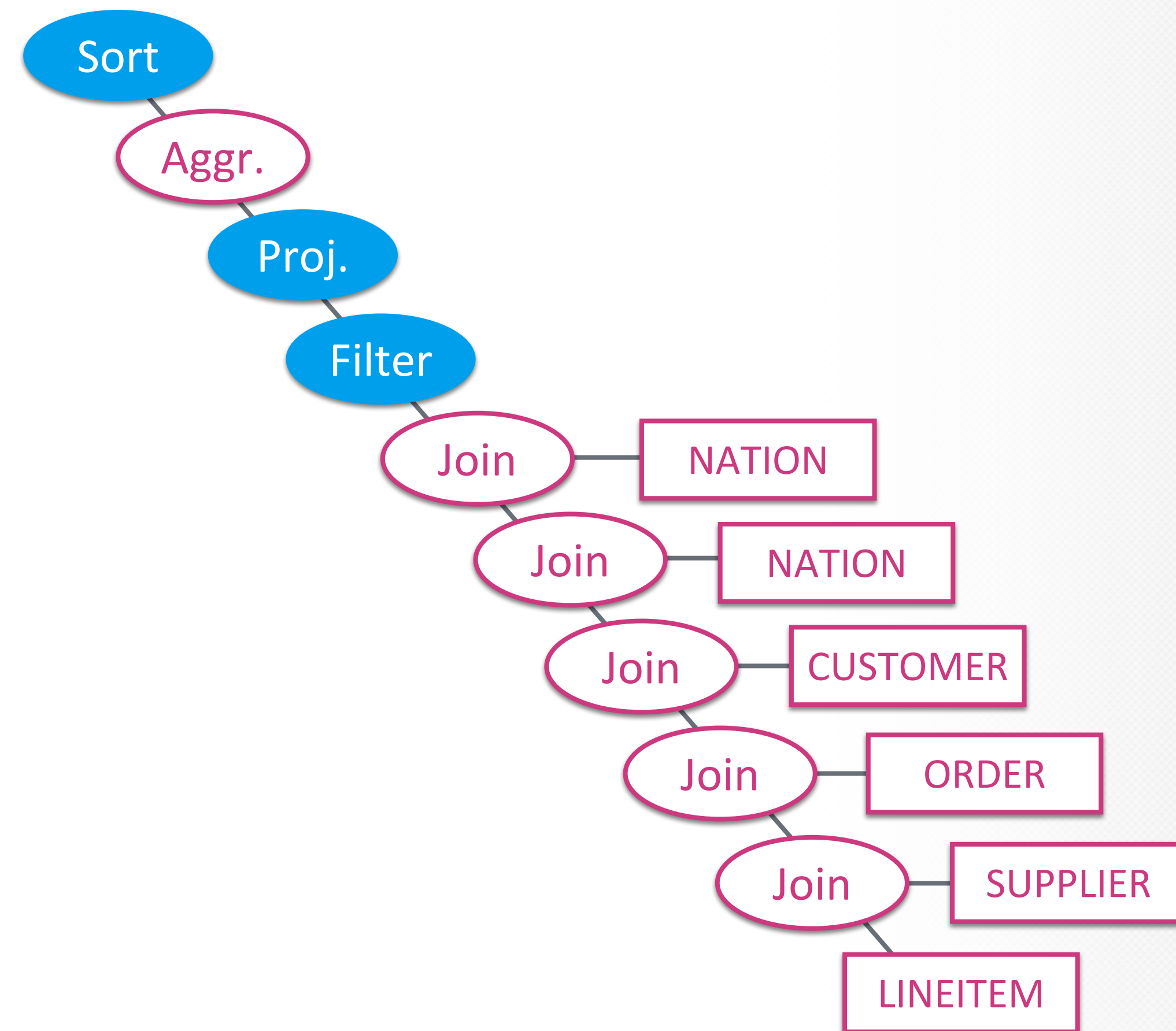


复杂查询 1

TPC-H query 07

- 0.17 sec (Hive+Tez 35.23 sec)
- 2 sub-queries

```
select
  supp_nation,
  cust_nation,
  l_year,
  sum(volume) as revenue
from
(
  select
    n1.n_name as supp_nation,
    n2.n_name as cust_nation,
    l_shipyear as l_year,
    l_saleprice as volume
  from
    v_lineitem
    inner join supplier on s_suppkey = l_suppkey
    inner join v_orders on l_orderkey = o_orderkey
    inner join customer on o_custkey = c_custkey
    inner join nation n1 on s_nationkey = n1.n_nationkey
    inner join nation n2 on c_nationkey = n2.n_nationkey
  where
    (
      (n1.n_name = 'KENYA' and n2.n_name = 'PERU')
      or (n1.n_name = 'PERU' and n2.n_name = 'KENYA')
    )
    and l_shipdate between '1995-01-01' and '1996-12-31'
  ) as shipping
group by
  supp_nation,
  cust_nation,
  l_year
order by
  supp_nation,
  cust_nation,
  l_year
```

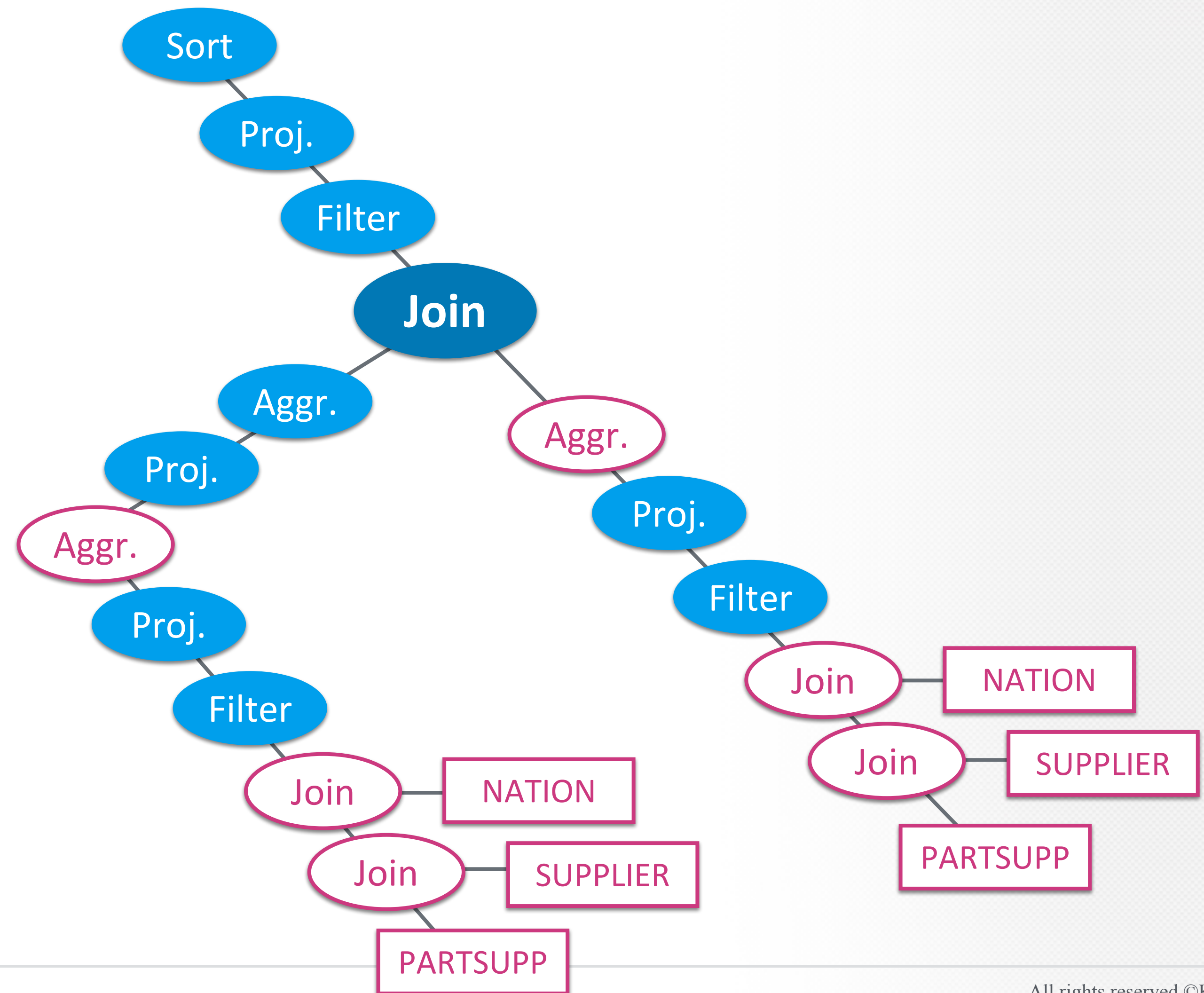


复杂查询 2

TPC-H query 11

- 3.42 sec (Hive+Tez 15.87 sec)
- 4 sub-queries, 1 online join

```
with q11_part_tmp_cached as (  
  select  
    ps_partkey,  
    sum(ps_partvalue) as part_value  
  from  
    v_partsupp  
    inner join supplier on ps_suppkey = s_suppkey  
    inner join nation on s_nationkey = n_nationkey  
  where  
    n_name = 'GERMANY'  
  group by ps_partkey  
)  
q11_sum_tmp_cached as (  
  select  
    sum(part_value) as total_value  
  from  
    q11_part_tmp_cached  
)  
select  
  ps_partkey,  
  part_value  
from (  
  select  
    ps_partkey,  
    part_value,  
    total_value  
  from  
    q11_part_tmp_cached, q11_sum_tmp_cached  
) a  
where  
  part_value > total_value * 0.0001  
order by  
  part_value desc;
```



复杂查询 3

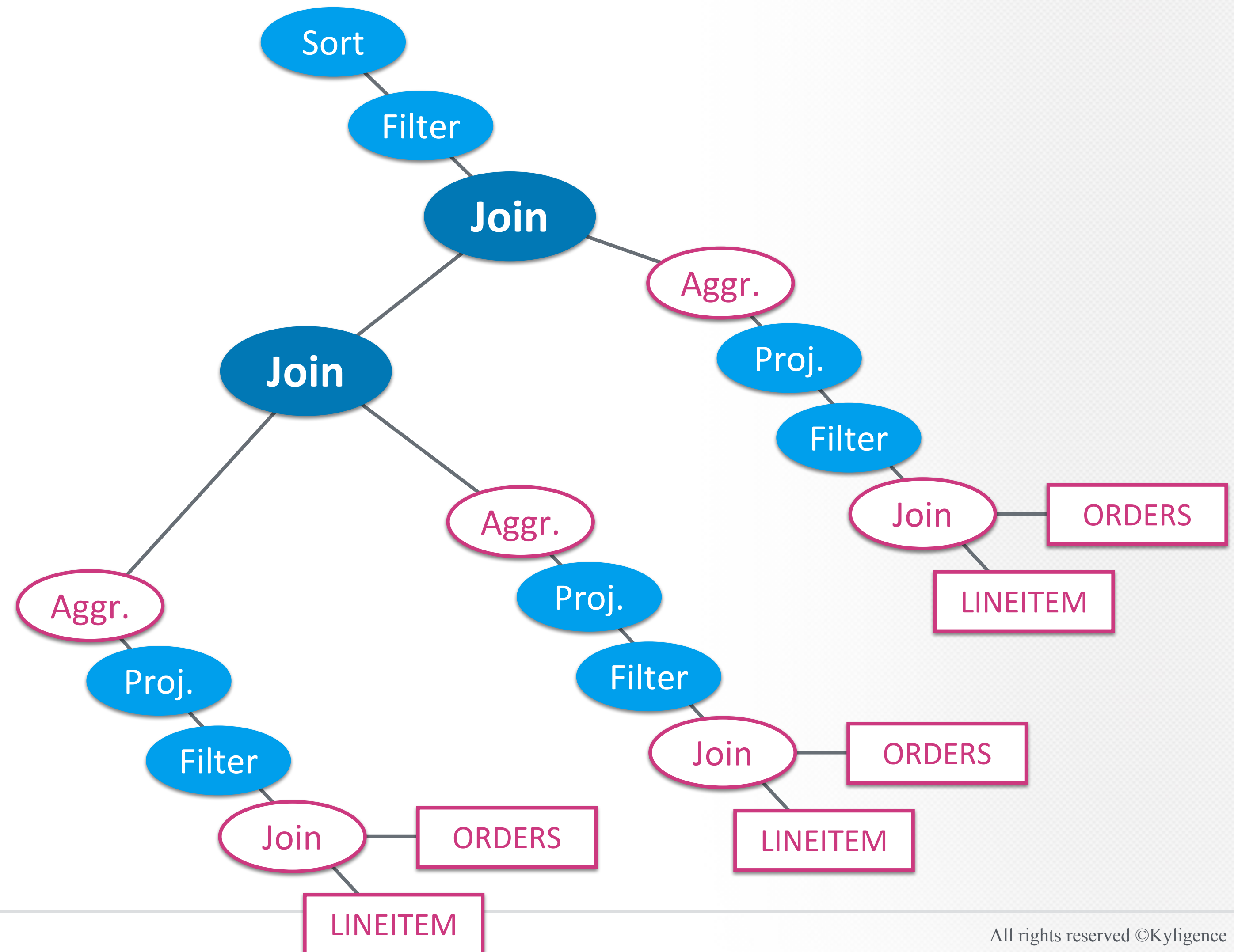
TPC-H query 12

- 7.66 sec (Hive+Tez 12.64 sec)
- 5 sub-queries, 2 online joins

```

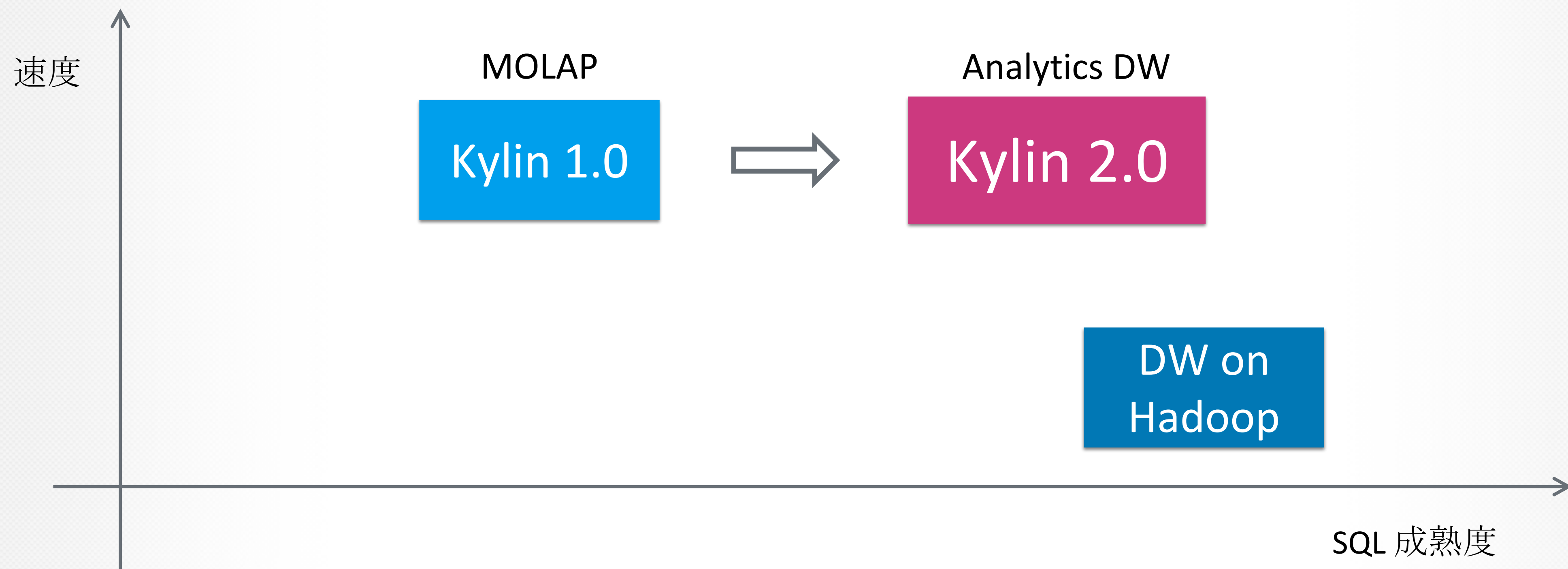
with in_scope_data as(
    select
        l_shipmode,
        o_orderpriority
    from
        v_lineitem inner join v_orders on l_orderkey = o_orderkey
    where
        l_shipmode in ('REG AIR', 'MAIL')
        and l_receiptdelayed = 1
        and l_shipdelayed = 0
        and l_receiptdate >= '1995-01-01'
        and l_receiptdate < '1996-01-01'
), all_l_shipmode as(
    select
        distinct l_shipmode
    from
        in_scope_data
), high_line as(
    select
        l_shipmode,
        count(*) as high_line_count
    from
        in_scope_data
    where
        o_orderpriority = '1-URGENT' or o_orderpriority = '2-HIGH'
    group by l_shipmode
), low_line as(
    select
        l_shipmode,
        count(*) as low_line_count
    from
        in_scope_data
    where
        o_orderpriority <> '1-URGENT' and o_orderpriority <> '2-HIGH'
    group by l_shipmode
)
select
    al.l_shipmode, hl.high_line_count, ll.low_line_count
from
    all_l_shipmode al
    left join high_line hl on al.l_shipmode = hl.l_shipmode
    left join low_line ll on al.l_shipmode = ll.l_shipmode
order by
    al.l_shipmode

```



超越 MOLAP

- 支持复杂模型和子查询; TPC-H 兼容
- Percentile / Window / Time 函数



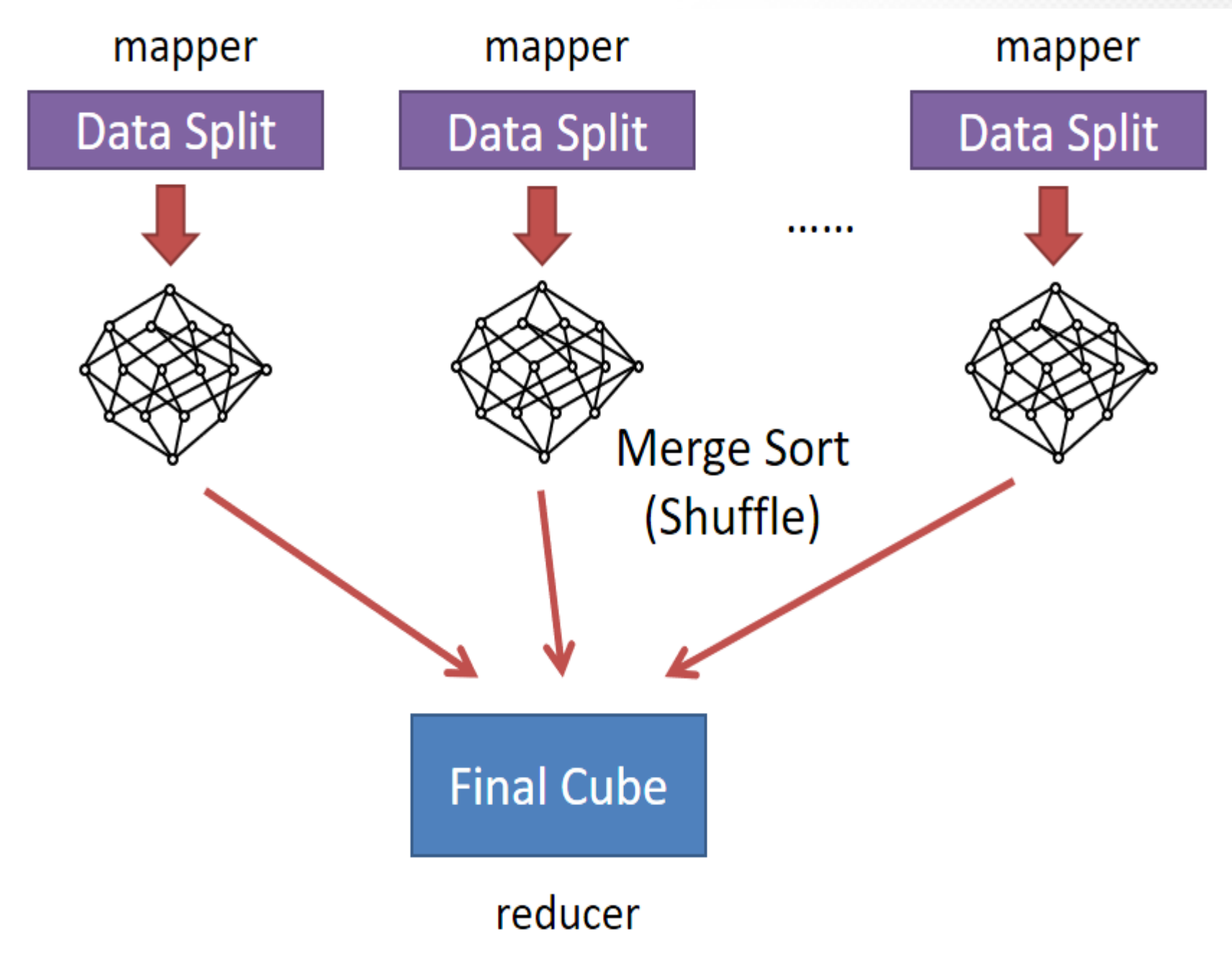
Spark Cubing

构建时间减半

一点历史

Kylin 1.5 就尝试过 Spark 构建，但这个功能从未发布

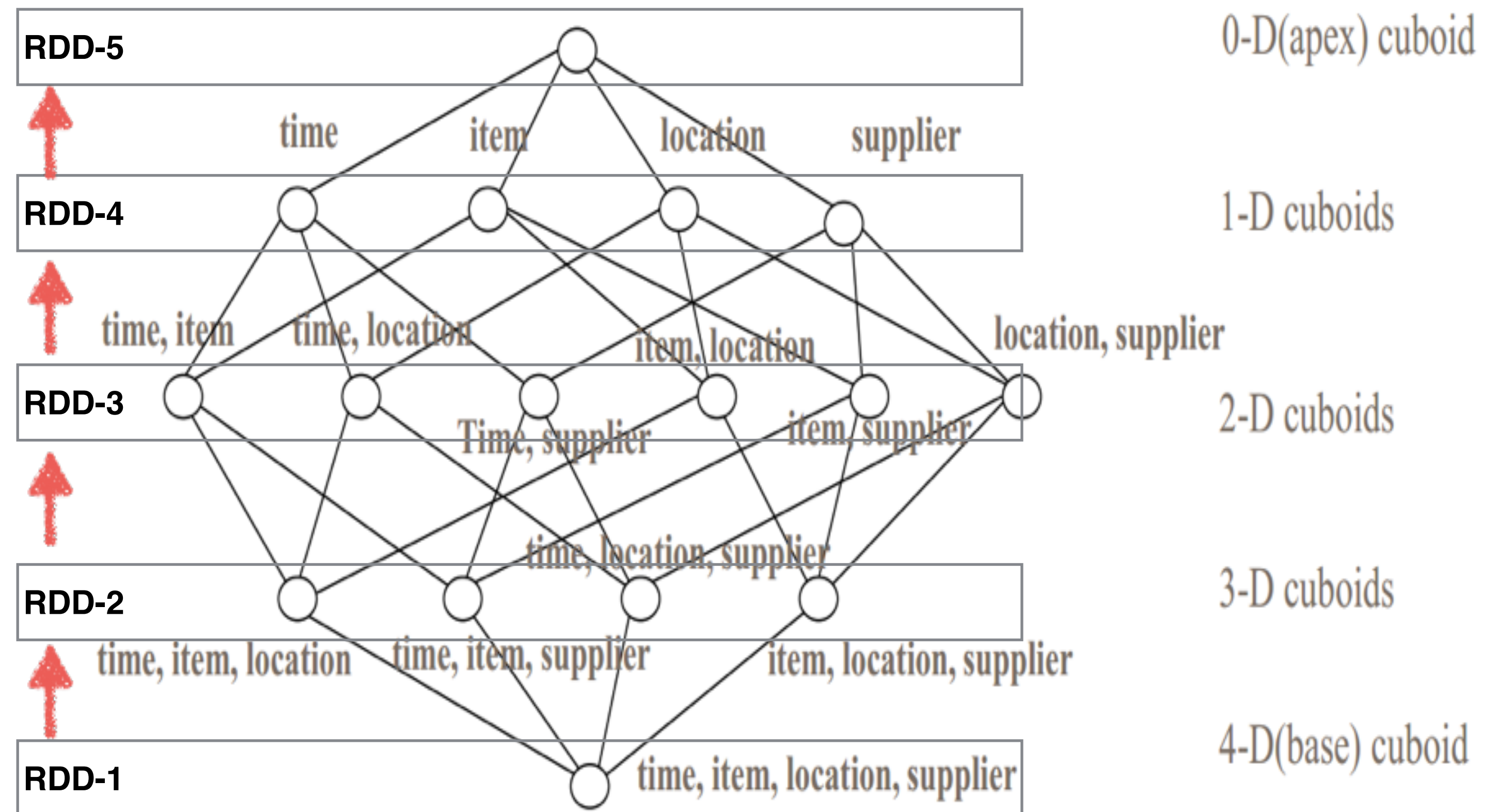
- 移植了 MR in-mem cubing 构建算法
- 占用内存，用一轮 MR 完成全部 Cube 构建
- 没有明显的性能提升
- 因为这里 Spark 与 MR 并没有什么不同



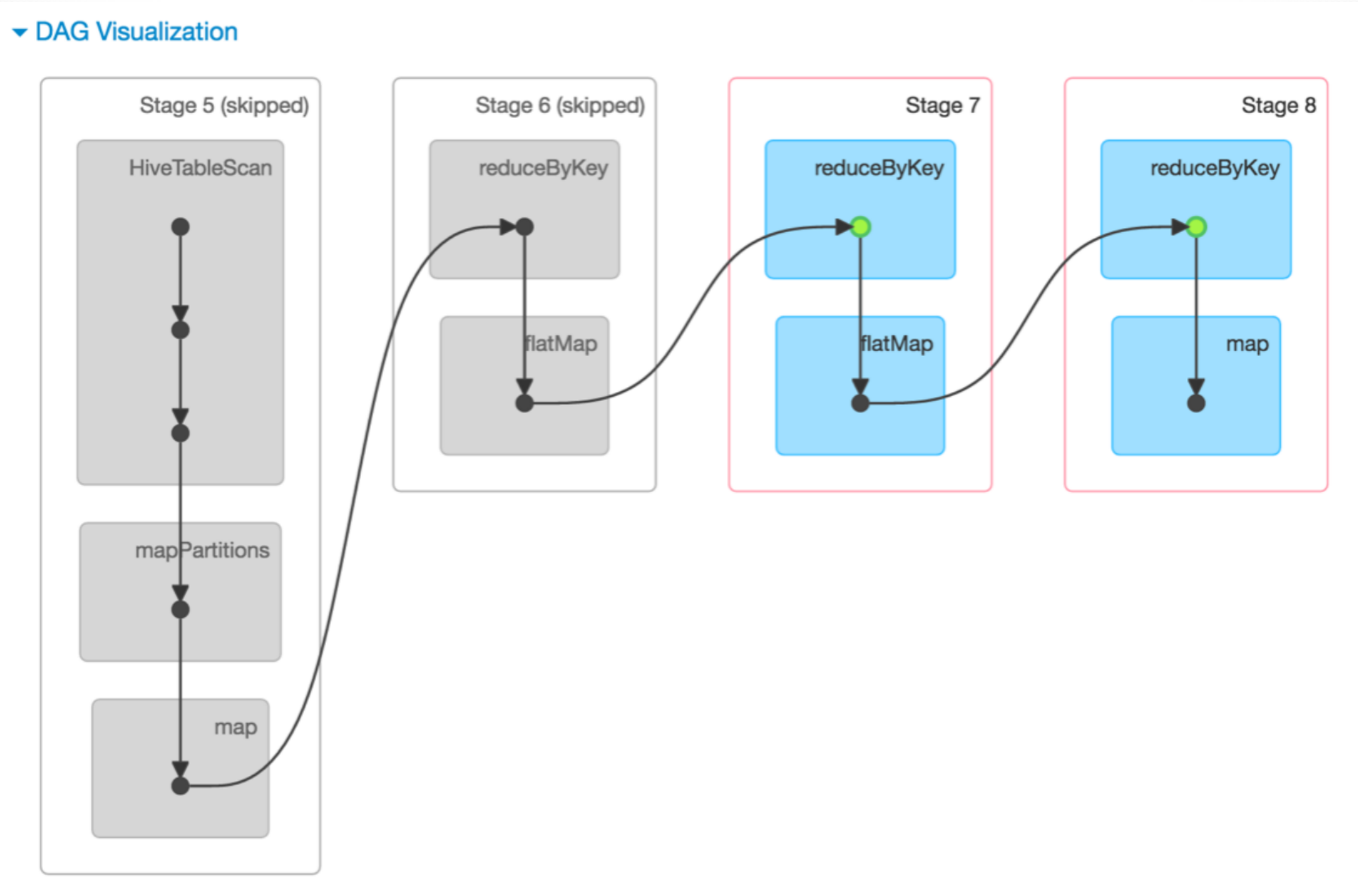
2.0 中的 Spark Cubing

Kylin 2.0 基于 Layered Cubing 构建算法重新实现了 Spark 构建引擎。

- 每一层 cuboids 是一个 RDD
- 前继 RDD 被缓存来加速下一轮
- RDD 最终被保存为 sequence file, 格式与 MR 兼容
- 重用代码, “map” to “flatMap”; “reduce” to “reduceByKey”



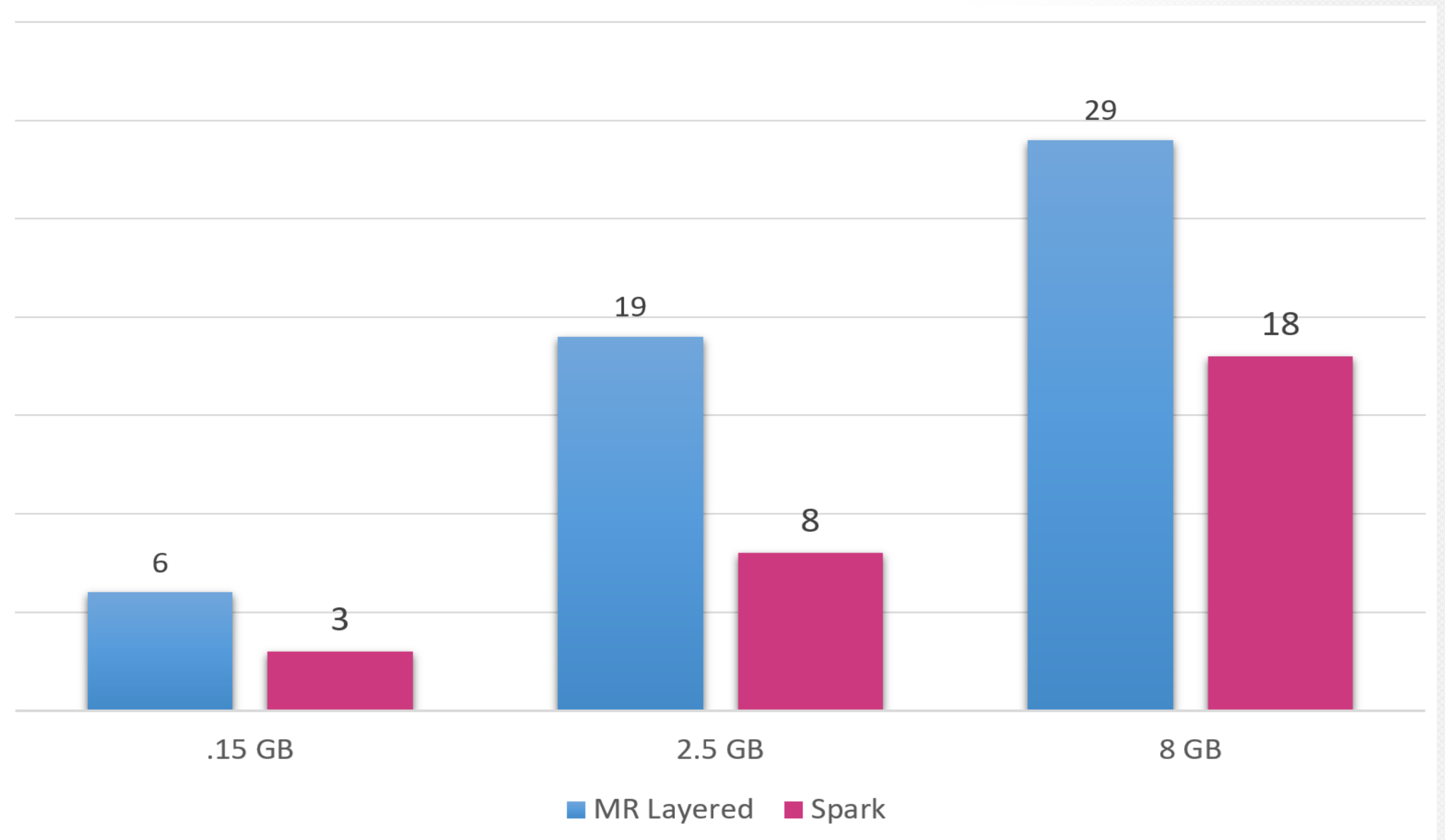
例子：计算第3层的 DAG



Spark Cubing vs. MR Layered Cubing

构建时间减半。优势随着数据量的增加而缩小。

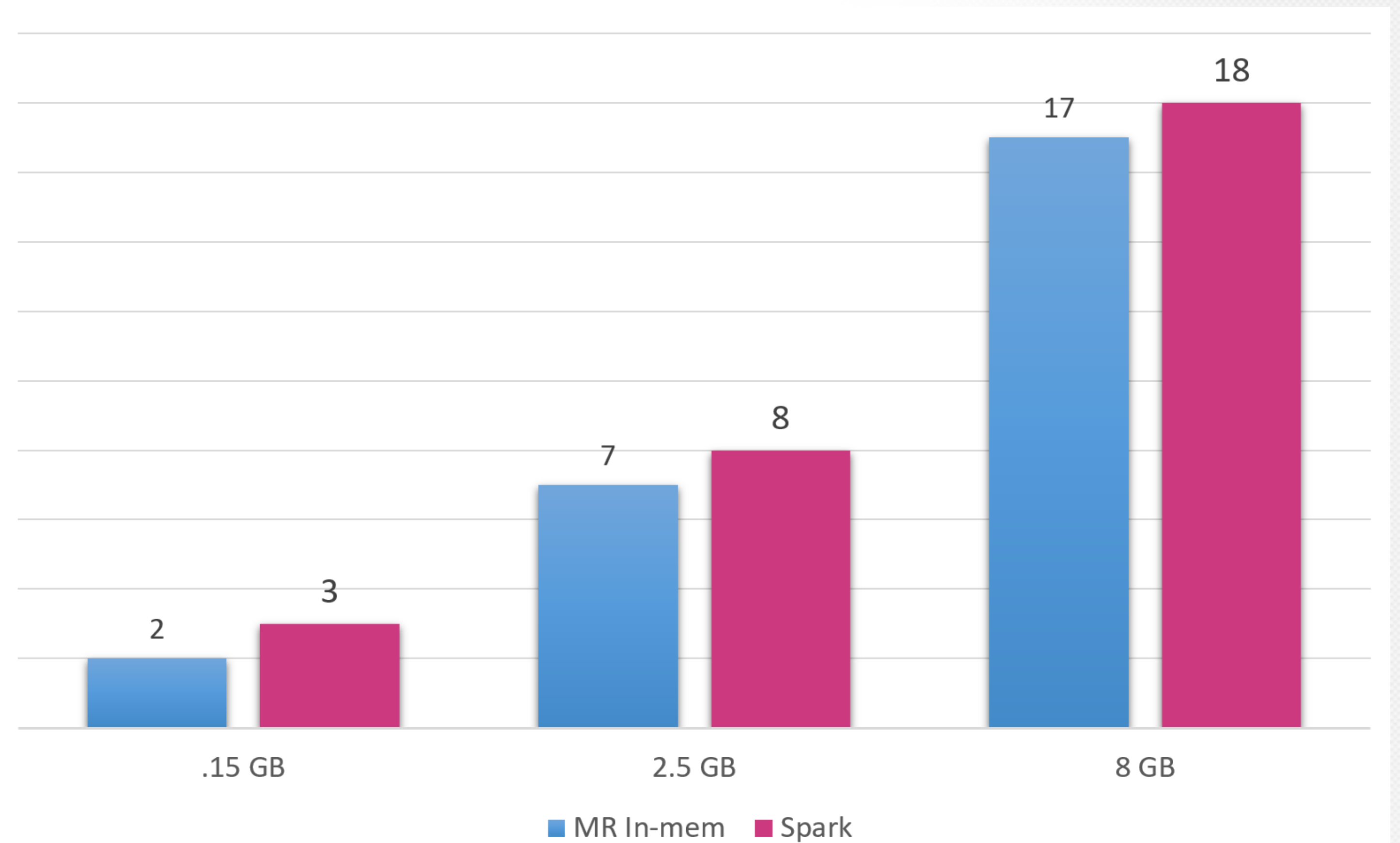
- 4-node cluster
- Spark 1.6.3 on YARN
- 24 vcores, 30 GB memory
- 测试 3 个不断增大的数据集
.15 GB / 2.5 GB / 8 GB



Spark Cubing vs. MR In-mem Cubing

Almost the same fast. And more adaptable to general data set.

- In-mem cubing expects sharded data, works poorly on random data sets.
- Spark cubing is more adaptable to different kinds of data distribution.

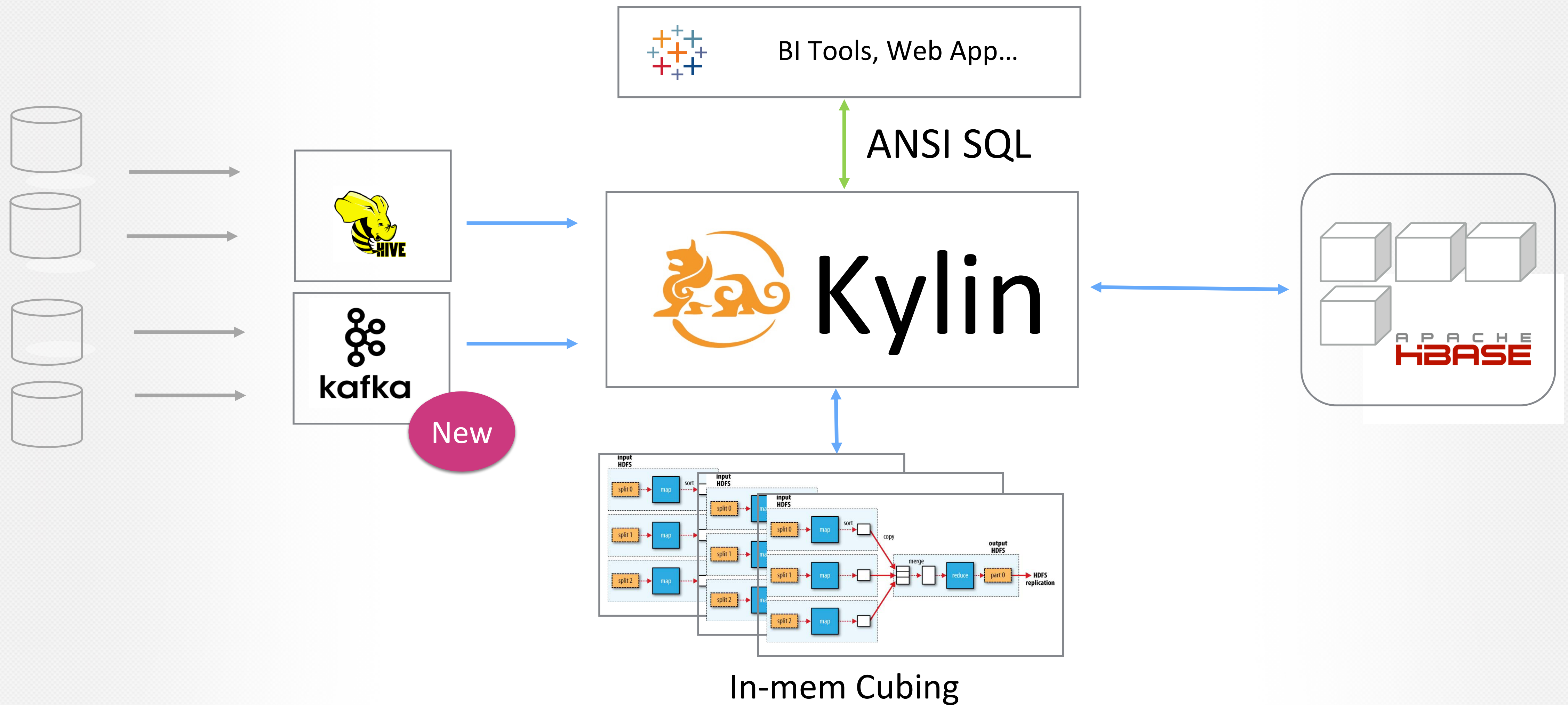




近实时流式构建

延时缩短到几分钟

Kylin 1.6 中的新功能



演示：Twitter 实时分析

<http://hub.kyligence.io>

增量构建每 2 分钟一次，每次耗时 3 分钟。

- 8-node cluster on AWS, 3 Kafka brokers
- Twitter sample feed, 每秒 10+ K 记录
- Cube 有 9 个维度和 3 个度量
- 2 个构建任务并发执行

Jobs in: LAST ONE WEEK ☐ NEW ☐ PENDING ☐ RUNNING ☐ FINISHED ☐ ERROR ☐ DISCARDED					
Cube ↕	Progress ↕	Last Modified Time ▼	Duration ↕	Actions	
embedded_cube	73.68%	2016-10-10 21:52:28 PST	1.65 mins	Action ▼	
embedded_cube	5%	2016-10-10 21:52:23 PST	0.23 mins	Action ▼	
twitter_tag_cube2	100%	2016-10-10 21:44:19 PST	5.37 mins	Action ▼	
embedded_cube	100%	2016-10-10 21:44:14 PST	3.27 mins	Action ▼	
twitter_tag_cube2	100%	2016-10-10 21:38:15 PST	7.28 mins	Action ▼	
embedded_cube	100%	2016-10-10 21:37:38 PST	2.83 mins	Action ▼	
embedded_cube	100%	2016-10-10 21:34:26 PST	3.48 mins	Action ▼	
embedded_cube	100%	2016-10-10 21:24:14 PST	3.27 mins	Action ▼	

Real-Time Streaming Analytics for Twitter

请选择时间:

Sat, 11 Mar 2017 09:12:59 GMT



-

Sun, 12 Mar 2017 09:12:59 GMT



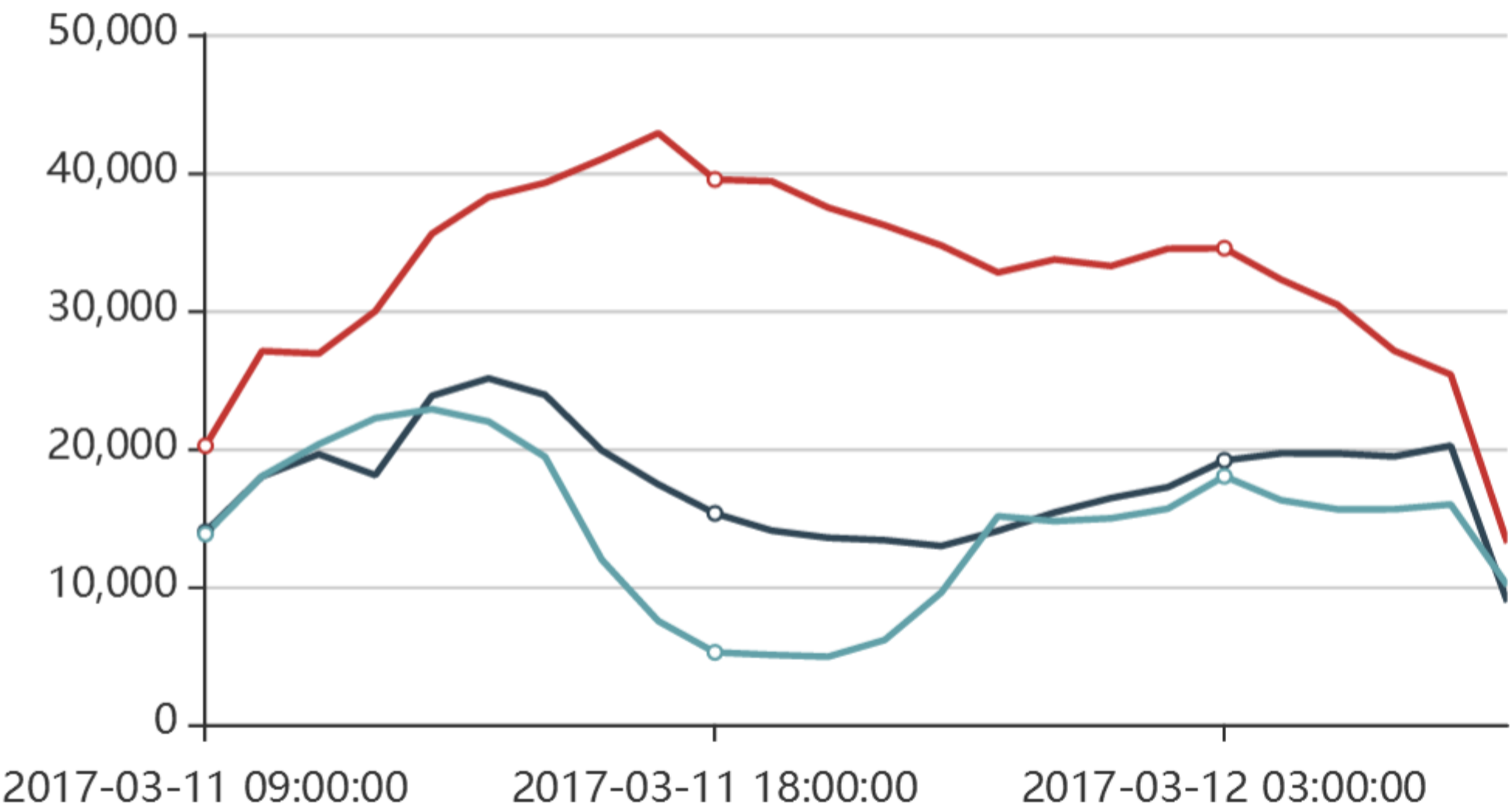
每五分钟刷新一次

* 以当前时间选择,计算时自动转化为GMT格式时间

Language

en, ko, ja ▼

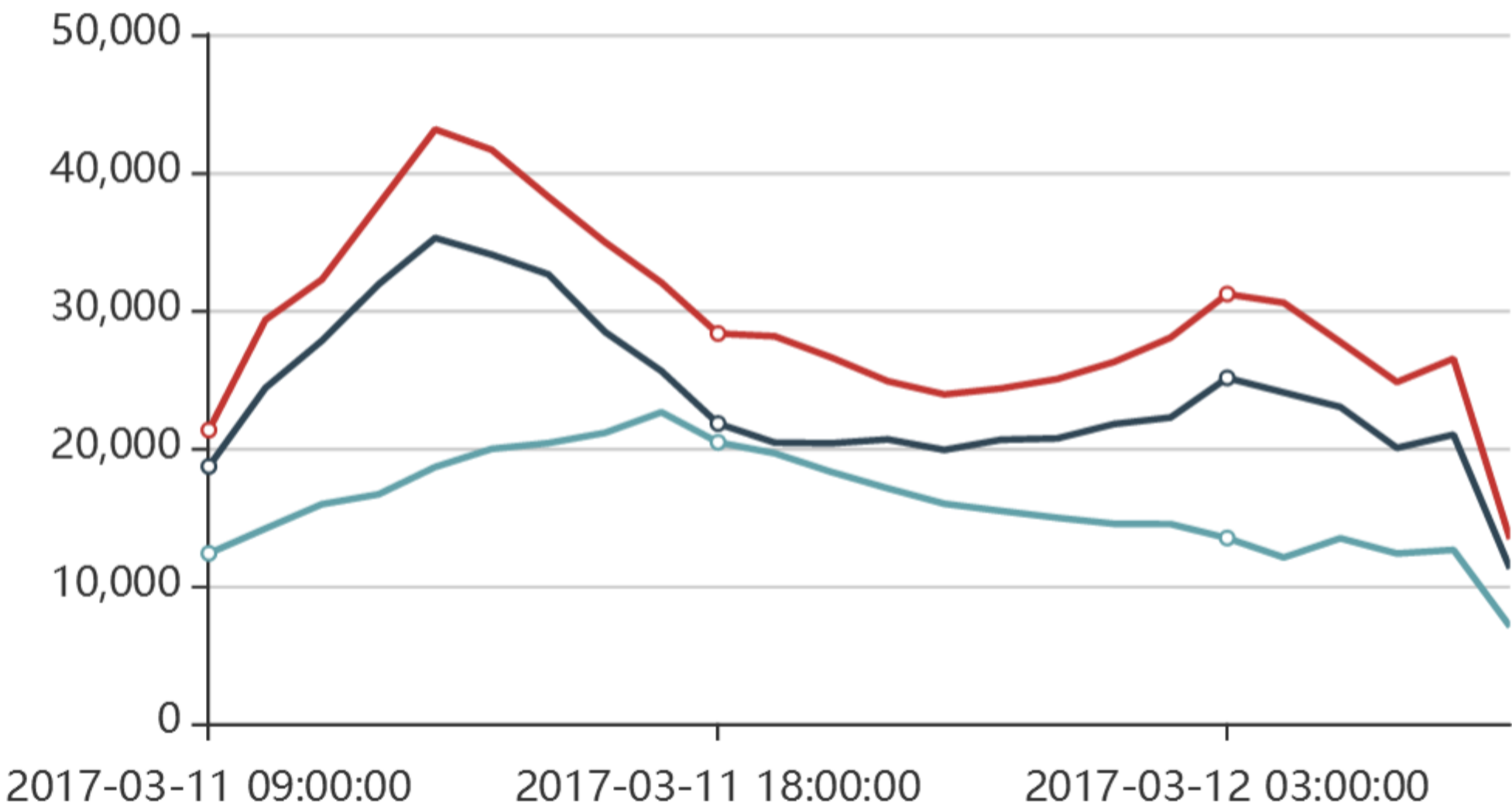
—○— en —○— ko —○— ja



Device

Twitter for Android, Twitter for iPhone, Twitter Web Client ▼

—○— Twitter for Android —○— Twitter for iPhone —○— Twitter Web Client



en ▼

[illegible]

[VideoLove](#)
[x](#)
[NadineForSonyXBass](#)
[x](#)
[Mashup](#)
[x](#)
[TVDForever](#)
[x](#)
[MGK](#)
[x](#)

NadineForSonyXBass x

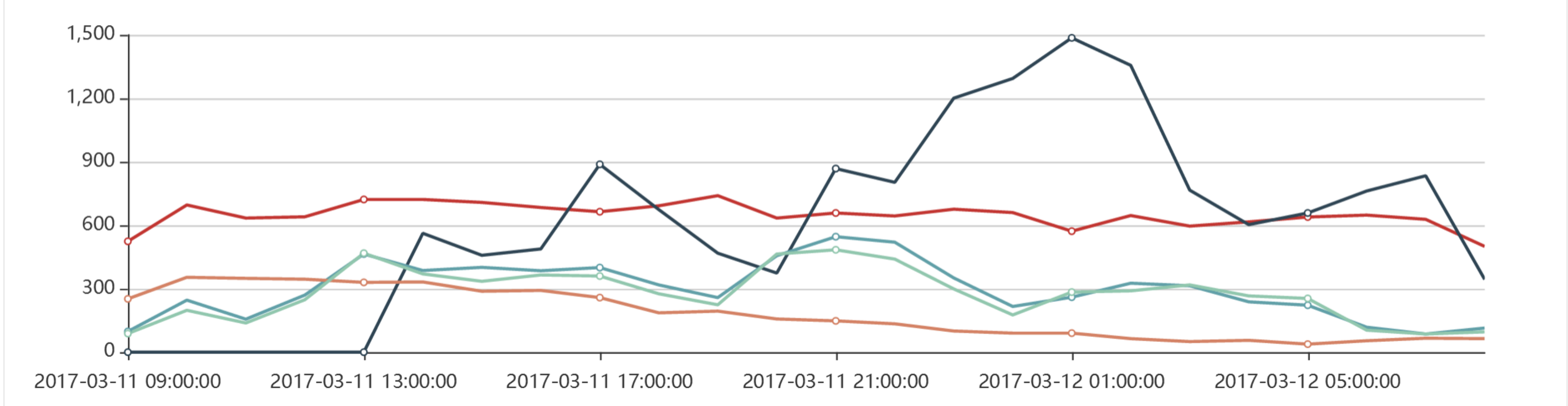
Mashup x

TVDForever x

MGK x



— VideoLove — NadineForSonyXBass — Mashup — TVDForever — MGK



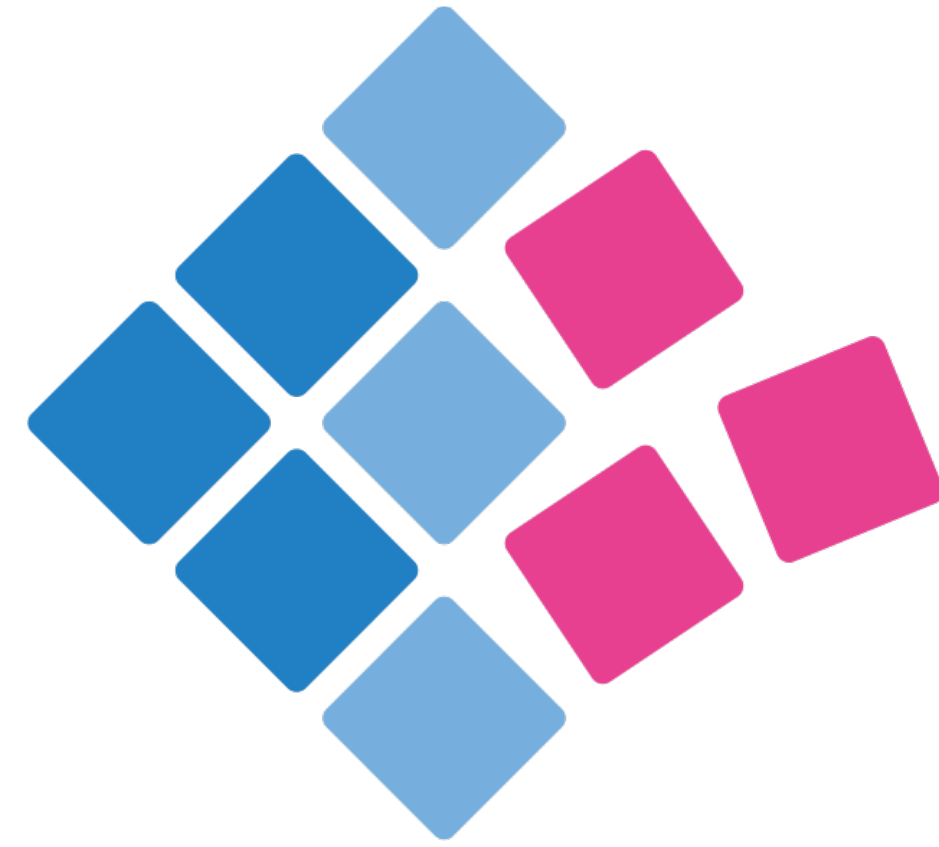
小结

Apache Kylin 2.0

- [Kylin 2.0 Beta download](#) 已经可以试用
- 支持雪花模型
- 运行 TPC-H 基准测试
- Time / Window / Percentile 函数
- Spark 构建引擎
- 近实时数据分析

What is next

- Hadoop 3.0 支持 (Erasure Coding)
- Spark 构建引擎持续改进
- 连通更多数据源 (JDBC, SparkSQL)
- 不同的存储 (Kudu?)
- 零延迟实时分析, Lambda 架构



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